Novel Approach for Detection and Tracking of Explosive Carrying Mobile Humans with Odor-Sensor Based Multisensor Networks

Ahmet KUZU
Control Engineering
TUBITAK-MAM-BTE
PK21 41470 Gebze/Kocaeli
TURKEY
ahmet.kuzu@bte.mam.gov.tr

METIN GOKASAN
Electrical & Electronics Eng. Fac.
Istanbul Technical University
Maslak 34469, Istanbul,
TURKEY
gokasan@itu.edu.tr

Seta BOGOSYAN
Electrical & Computer Engineering
University of Alaska Fairbanks
Duckering Building 221 Fairbanks
AK 99775-5915 USA
ffsob@uaf.edu

Abstract: - In this study, a distributed system which could be used to detect and track an explosive carrying mobile human is designed. As a novel approach to existing odor detection and tracking methods, a technique which combines odor and sound detection is proposed for increased accuracy. To this aim, a MEMS sensor network including a pressure sensor, an accelerometer, a microphone, an odor sensor and electronic unit is proposed. For the electronic unit of this system a sensor network and least square estimation based sensor fusion algorithm is developed and simulated. The results are evaluated with respect to various paths of two humans, one carrying the explosive. The results show that odor sensing alone is not sufficient for the accurate determination of the odor track, and that by adding other conventional tracking methods, accuracy could be increased.

Key-Words: - Odor, Tracking, Sensor networks, Sensor fusion, Least squares, Explosive

1 - Introduction

Although there is sufficient technology to detect metal weapons, detection of plastic explosives such as C-4 with methods that are harmless to humans, still remains to be a challenge. Metal detectors or X-ray facilities commonly used at airports and customhouses cannot find plastic explosives. Y-ray detection using irradiation of neutron beams is recognized as an effective method for C-4 detection at this point, but few actually use this method due to doubts about the safety of using nuclear radiation on the public. Hence, methods must be sought to carry out C-4 inspection safely, nondestructively, and without physical contact. One possible method is the use of THz radiation, which is claimed not to harm the human body in [1].

Detection of explosives using odor sensors is already in use for the detection of land mines and there has been ongoing research on odor sensor based detection of plastic explosives [2][3],[4],[5], which mostly develop ways to detect the different odorants in a specific odor.

There are numerous studies in the literature for odor source localization; some studies try to locate the odor source by triangulation [6], while some studies try stochastic estimation techniques like Least Square Estimation Method [6] and Maximum Likelihood Method [7], or Bayesian based methods like PQS (Process Query System) [8]. A common characteristic in all these algorithms is their low accuracy and sensitivity to environmental effects like the wind.

The major contribution of this study is the development of a method that could be used with odor-sensor based microelectromechanical (MEM) sensor networks for the detection and tracking of a human carrying a plastic explosive while moving among several other mobile, unarmed humans. In this study, it is also demonstrated that combining odor detection with sound detection will provide higher accuracy than finding the odor source directly, with the use of odor detection alone. In the developed algorithm, commonly used passive target tracking techniques such as acoustic, seismic and pressure based techniques are fused to accurately detect and track the target trajectory. These targets are then matched with the odor detection results, which are obtained via the conventional triangulation method. The resulting performance provides a higher accuracy in comparison to other odor source localization techniques reported in the literature

Another contribution of the study is the detection and tracking of mobile odor sources (i.e explosives in this case) with the use of stationary sensors, unlike most studies in which stationary targets are pursued using mobile sensors [9]. This approach will also increase the chances of tracking and disarming the intruder without his/her awareness and at an appropriate moment and will significantly limit the harm caused to innocent bystanders and security officers. The use of odor sensors will further contribute to optimize energy consumption in the network in that all sensor groups in the module will be kept on standby, unless a command is received from the odor sensor.

This study will combine these approaches for the aim of accurate detection and tracking of a human carrying an explosive in a public place. To this aim, a multisensor network (MSN) will be designed based on n-MEM sensor modules; each MEM sensor module will include low-cost, low-power passive sensors, namely odor sensors for the detection of the explosive, and a microphone, accelerometer, passive infrared sensors (PIRs) and a pressure sensor for the tracking of the human carrying the explosive. Each MEM module will also include circuitry for the data fusion of the odor sensors, signal conditioning circuitry as well as RF communication and power supply circuitry in the same case. Signal conditioners will convert sensor outputs in each module to appropriate levels, which are then processed via analog-to-digital converters (ADCs). Data from the odor sensors will also undergo a fusion process. The fused data will then be transmitted from each module, along with the outputs of the multiple sensors to the hub unit, via RF transmission. This unit is the major processing unit located in each subdivision of the network and performs fusion and decision tasks, while also conducting communication with each sensor module, other hub units in the network and the base computer for higher level data fusion and decision-making. This process will be further discussed in the "Proposed multisensor networking and sensor/data fusion approaches" section. A functional block diagram of the process is given in Figure 1.

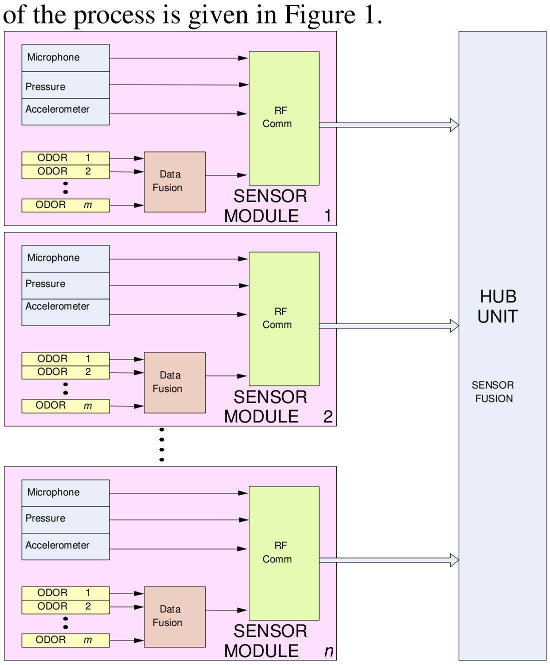

Figure 1. Functional block diagram of each MEM sensor module and hub unit

Four different sensor types are considered for each MEM sensor module; namely, odor sensor, microphone, accelerometer [10], and pressure sensor. Structural diagram of this mechatronic module is shown in Figure 1. Odor sensors detect the explosives while microphones serve as passive radars, which detect the location of mobile objects from their vibrations in the air. Accelerometers, which detect seismic waves, also serve the same purpose. Finally, pressure sensors are activated upon direct contact, in that sense; they produce highest accuracy and hence, are also used to calibrate the other sensors. The Zigbee Network protocol [11], in RF Communication Block, is used to collect the sensor data, which are then used in fusion and decision algorithms [12]. The Rf Communication block also supplies sensor localization by using trianglization method [13,14].

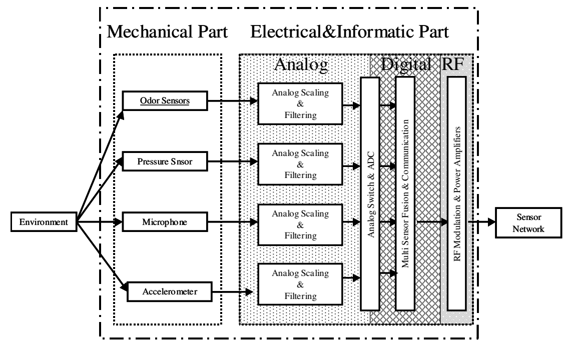

Figure 2: Structural diagram of this mechatronic module.

The odor sensor is comprised of a sensor array [15] to measure the density of a variety of odorants constituting an odor, a classifier to fuse and classify the collected data [16,17]; This sensor detects the odor of weapon, and estimate the source of odor. [18]. Although the resolution of odor sensors is lower than the other sensors, their use in combination with the odor sensor for the approximate localization of the target proves to be very effective as demonstrated by simulations in this study.

The following sensors is designed individually and then, combined in a single case to constitute the above mentioned MEM sensor module:

Sound sensors (MEM microphones): A microphone is a sensor, which converts acoustic pressure to voltage by using a thin diaphragm. When voice pressure strikes a diaphragm, stress and depletion occurs. This stress can be easily measured by piezoresistors, or depletion can be detected by capacitance change. Figure 3 depicts the architecture of a piezoresistive microphone. Signals output by the microphone provide some information on the position of the intruder based on the duration of time required for the intruder-transmitted sound waves to arrive at the microphone. This data component will be further fused with data produced by other sensor modules at different locations to yield the position of the intruder. The need for other sensors in addition to the sound sensor arises from the fact that sound waves are subject to losses and reflection; reliable detection and tracking requires the ability to filter out these effects.

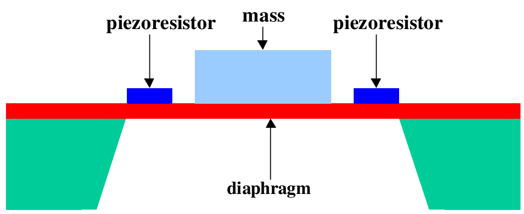

Figure 3. MEM Piezoresistive Microphone.

Pressure sensors: Pressure sensors, given Figure 4, operate on the same principles as microphones. The main difference is the strength and resonance frequency of the diaphragm. The pressure sensors operate as logic sensors, giving the exact position of the intruder (if stepped upon), hence serving as a calibrator for the other sensors.

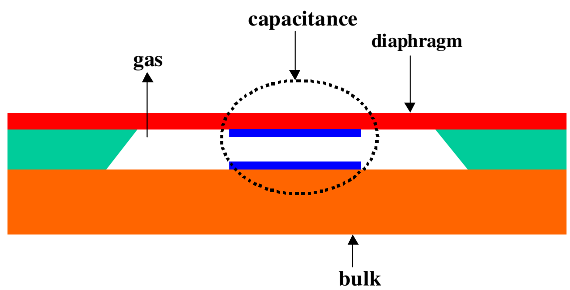

Figure 4. MEM Capacitive Pressure Sensor

Accelerometers: When acceleration occurs, proof mass applies force on the beam, giving rise to stress and depletion. This stress can be easily measured by using piezoresistors, or depletion can be detected by its capacitance change. The architecture of a MEM piezoresistive accelerometer appears in Figure 5, which demonstrates how this system will be used to sense motion in a certain area via vibrations on the ground. The PI and her PhD student have already designed a MEM multiple accelerometer module, also including the data fusion and RF circuitry in the same case. The product is currently under testing.

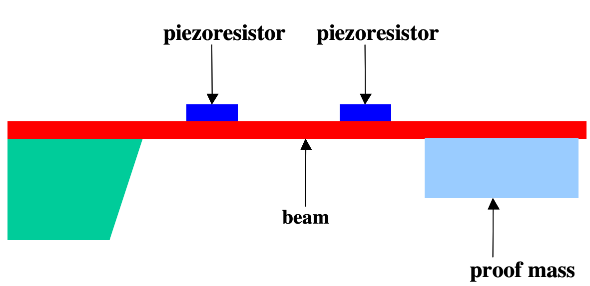

Figure 5. MEM Accelerometer.

Odor Sensors: These sensors operate based on odorants. Each odorant compound signifies a different odor. Typical ways of measuring odor is by designing filters for the desired odorants, and placing a sensor at the output of each filter (see Figure 6 for a demonstration of this process). For instance, if a capacitive sensor is used, the capacitance value varies based on the action of these odorants, which affects the dielectric part of the capacitance, as demonstrated in Figure 7. Each odor consists of one or more odorant types. For instance Odor 1 can consist of 30-40% Odorant A and 77-79% Odorant B. Another odor may consist of 50-55% of Odorant A and 20-25% Odorant B. Hence, recognizing an odor requires more than one sensor and the fusion of their outputs.

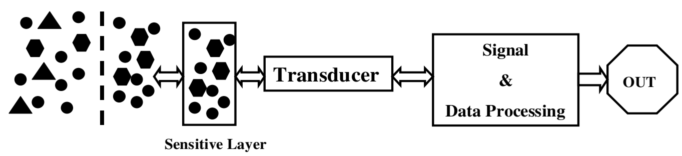

Figure 6. Odor Measurement Process.

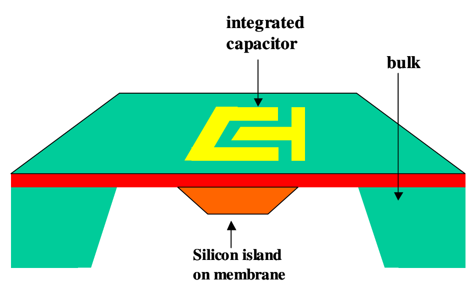

Figure 7. MEM Odor Sensor.

There are basically five different odor sensing methods: Conductivity Sensors, Piezoelectric Sensors, Metal-oxide-silicon field-effect-transistor (MOSFET), Optical Fiber Sensors, and Spectrometry-Based Sensors. Methods for odorant sensing under consideration in this study are the following: One method is measuring the change in the dielectric coefficient of a certain polymer which reacts with the certain odorant. The dielectric coefficient can be easily measured by making a capacitance using this polymer. The proposed structure is given in Figure 8.

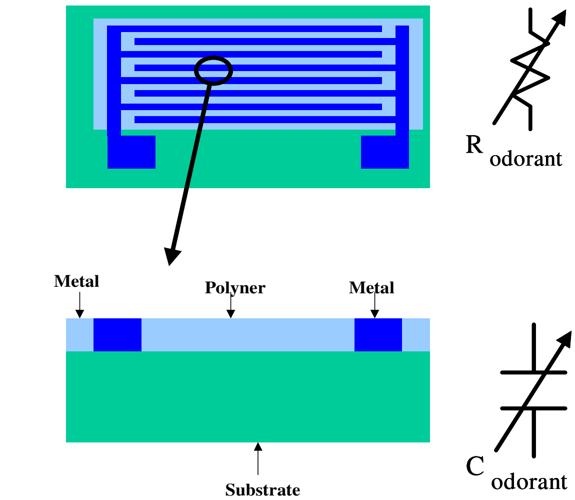

Figure 8. Structure of resistive and capacitive sensors and cross-sectional view

The second approach is measuring the resistance of a certain polymer which reacts with the certain odorant. By making a resistance using this polymer, the conductivity coefficient which changes as a result of the reaction can be measured. The structure is similar to the capacitance method, but a different polymer is involved. The third approach is measuring the chemical properties (like pH) of a special polymer to identify the odorant. Once again the appropriate polymer reacting to the odorant is chosen, but in this approach, the change in the chemical properties is measured by a chemical FET. The source drain current of the FET is affected by the chemical properties of the polymer. The structure of the chemical FET is given in Figure 9.

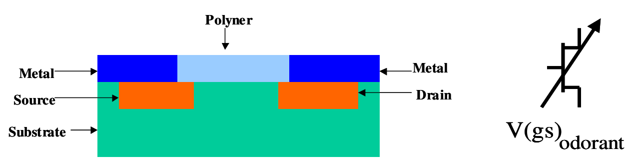

Figure 9. Chemical FET

The design of the MEM odor sensors in this study requires for a hybrid structure. Since the odor detection will require several odor sensors to be incorporated in the same module, with each sensor reacting to a different attribute of the explosive's odor, a data fusion algorithm taking place inside the module will also be developed to fuse the data from the odor sensor array.

For energy optimization purposes, the sensors and fusion/communication process in each module and in the sensor network will be activated only when the odor sensor in a sensor module indicates a potential explosive in that subdivision. Additionally, to minimize the energy consumption, the fused data in each SM is transferred to the hub unit via the neighboring SMs . Hence, in the 1st year, the duties of each SM involve sensing motion and odor, detecting odor and passing on its data and data from other SMs to the hub unit.

Hub Units (HU): These units possess a higher processing power and memory in comparison to the sensor modules and conduct the fusion of data coming from sensor modules in its subdivision. HUs are also equipped with power and wireless communication circuitry. Each HU is in charge of a certain subdivision (indicated by the circles in Figure 10), hence, collects data coming from SMs related to the location of the target and odor of the explosive to further perform data fusion and decision-making for the proper determination of the "mobile" explosive's motion trajectory. This information is then transmitted to the neighboring HUs and the base. For optimized energy consumption, the transmission of the data to the base is also done via other HUs, where all data is fused for decision-making.

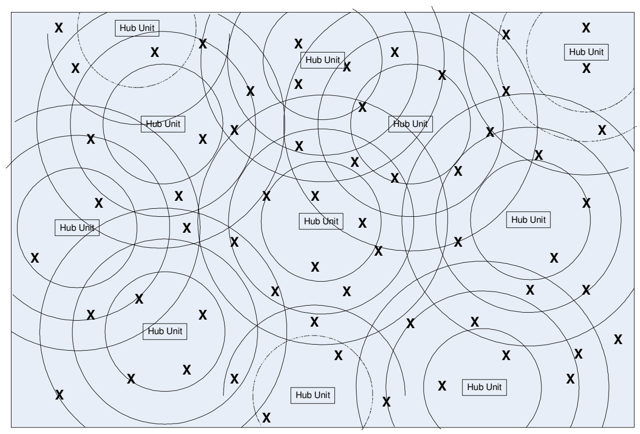

Figure 10. Sample configuration of the MEM-MSN

2 - Physical Model for Intruder Detection and Tracking using Sound Sensors and Accelerometers Used In Simulation

Figure 11 gives a configuration example for the random locations of the sensor modules, hub unit and the explosive–carrying human (intruder). As will be demonstrated with the derived equations, the location of the intruder is determined with a minimum of 3 sound sensors, denoted by S_1, S_2, and S_3, the data from which is fused at the hub unit via Least Square Estimation. The hub unit in that sense is assumed to be just another sound sensor, which hears the intruder as soon as any one of the sensors sends it a signal. In the simulations, S1 is assumed to have heard the intruder first; hence, both S1 and hub unit are assumed to hear the intruder in *dT* seconds**.** As can be seen in Figure 1, the unknown distance between the hub unit and the intruder is denoted by *d*.

The derivation of the equations are based on the notation used in Figure 12. The coordinate axes of the hub unit is taken as reference; x,y are the coordinates of the intruder, while (x_1,y_1), (x_2, y_2) and (x_3, y_3) are the coordinates of S_1, S_2 and S_3, respectively.

Sound is a traveling wave of pressure and can be modeled as,

$$f(d,v,t) = K(t)f(t) \quad (1)$$

where f(t) is the sound signal and K(t) is an amplitude coefficient which decreases in time; v is the velocity of sound, which is approximately 332m/s in the air at 20°C.

At an arbitrary instant, t, an intruder appears within the range of S_1 at a distance, d_1 from S_1 as demonstrated in Figure 2. At different time instants, S_2 and $S_3 \ldots S_{50}$ also hear the intruder, with d_2 denoting the distance between S_2 and intruder, d_3 denoting the distance between S_3 and intruder, and so on... dT denotes the arrival time of the sound at S_1 and hence, at the hub unit. dT_{12} denotes the arrival time differences between S_1 and S_2; dT_{23} denotes the arrival time differences between S_1 and S_3. Note that dT is unknown, while dT_{12} , dT_{23} are measured.

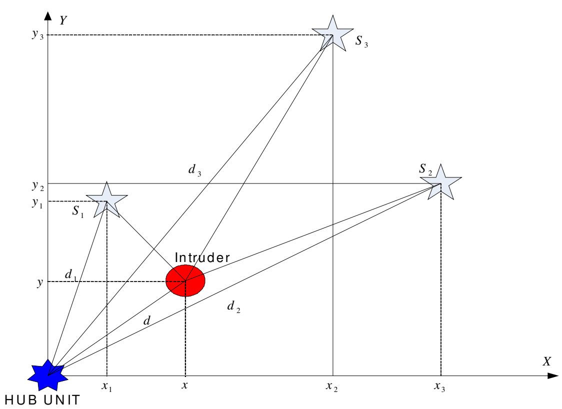

Figure 11. Configuration and definitions for intruder, sensors and hub unit

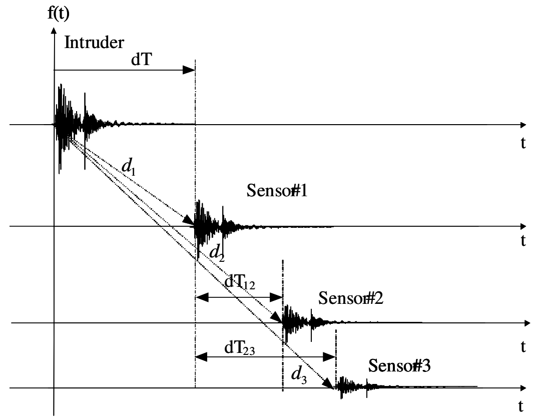

Figure 12. Intruder initiated sound waves with respect to sensors and hub unit

Base on these definitions, the following relationships can be derived:

$$d_1 = v(dT)\,,$$
$$d_2 = v(dT + dT_{12})\,,$$
$$d_3 = v(dT + dT_{23}) \quad (2)$$

Using (2), the following relationships can be given between each sensor and intruder coordinates:

$$(x - x_1)^2 + (y - y_1)^2 = (v(dT))^2 \quad (3)$$
$$(x - x_2)^2 + (y - y_2)^2 = (v(dT + dT_{12}))^2 \quad (4)$$
$$(x - x_3)^2 + (y - y_3)^2 = (v(dT + dT_{23}))^2 \quad (5)$$

Combining (3) with (4) we get (6), (3) with (5) we get (7), and (4) with (5) we get (8).

As can be seen from the equations, *x,y*, and *dT* are the unknown variables, while all terms on the right are known. Hence, it can be seen that determining the intruder's location in 2-dimensional spece requires 3 sensors, while 3-dimensional space would require a minimum of 4 sensors. At this point, to reflect the more realistic nature of sound velocity, *v*, which is actually dependent on the material and temperature, a white noise is added to the above equations and the solution is sought in terms of a Least Square Estimation problem.

$$2(x_2 - x_1)x + 2(y_2 - y_1)y + 2v^2(dT_{12})dT = -v^2 dT_{12}^2 - x_2^2 - y_2^2 + x_1^2 + y_1^2 \quad (6)$$
$$2(x_3 - x_2)x + 2(y_3 - y_2)y + 2v^2(dT_{23} - dT_{12})dT = -v^2 dT_{12}^2 + v^2 dT_{23}^2 - x_3^2 - y_3^2 + x_2^2 + y_2^2 \quad (7)$$
$$2(x_1 - x_3)x + 2(y_1 - y_3)y + 2v^2(dT_3)dT = v^2 dT_{23}^2 - x_1^2 - y_1^2 + x_3^2 + y_3^2 \quad (8)$$

$$2(x_2 - x_1)x + 2(y_2 - y_1)y + 2v^2(dT_{12})dT + \varepsilon_1 = -v^2 dT_{12}^2 + x_2^2 + y_2^2 - x_1^2 - y_1^2 \quad (9)$$
$$2(x_3 - x_2)x + 2(y_3 - y_2)y + 2v^2(dT_{23} - dT_{12})dT + \varepsilon_2 = -v^2 dT_{12}^2 + v^2 dT_{23}^2 + x_3^2 + y_3^2 - x_2^2 - y_2^2 \quad (10)$$
$$2(x_1 - x_3)x + 2(y_1 - y_3)y + 2v^2(dT_{23})dT + \varepsilon_3 = -v^2 dT_{23}^2 - x_1^2 - y_1^2 + x_3^2 + y_3^2 \quad (11)$$

2 - Physical Model for Intruder Detection and Tracking using Pressure Sensors In Simulation

Each module has a pressure sensor operating as logic sensors. In the experiments, they will be activated upon stepping and hence, serve as a calibrator for the other sensors and detection/tracking algorithm; however, in the simulations, these sensors are assumed to be activated when the intruder comes within a very close range of that certain point representing the sensor module. For example, in the presented simulation results, only S_5 (sensor 5) was stepped on.

3 - Preliminary model for odor diffusion and measurement in the simulations

Further assumptions in the simulations are that the explosives are emitting a gas constantly, which gives rise to a certain gas density at every instant, *t,* and this gas disperses into the environment by diffusion. Hence, a gas starting to disperse into the environment at t_1, will lose its effect in time but will exist forever. From the following instant, t_2 and on, new gas amounts will be effective cumulatively at any given point (or sensor module) in the environment.. The new gas amount will also disperse into the environment via diffusion, but with a reduced effect as time advances. Each odor sensor senses and measures the cumulative gas amount at that point.

Since Fick´s 2nd law is a partial differential equation with only a few analytical solutions available for special cases, numerical methods have to be used to apply it to technical problems. An analytical solution of Fick´s 2nd law is given by Equation (12): [19]

$$c(t,d) = c_\Gamma . erfc\left(\frac{d}{2\sqrt{Dt}}\right) \tag{12}$$

where c: dispersed gas amount, c_Γ : gas amount at source, d: distance from source, D: constant. In the simulations, odor is considered as a gas dispersing in amounts of Δc at every t. As the explosive-carrying human moves, at every point he/she moves at an new instant t, a new gas source, c_Γ starts its dispersion based on (12). A given odor sensor in the environment located at a distance, d from the intruder will accumulate n gas amounts, from n c_Γ sources, giving rise to a gas amount, S_i as expressed below:

$$S_i = \sum_{k=1}^{n} c_k(t,d) \tag{13}$$

Although a fusion and ANN based decision algorithm will be conducted for the multiple odor sensors in one module, only one odor sensor per module is considered in the simulations. Hence, for the determination of the coordinates for the explosive-carrying intruder, a weighted-average is performed combining the measured S_1, S_2, S_3, ...amounts collected from all odor sensors (50 in this case) at coordinates x_1, y_1, x_2, y_2, x_3, y_3... to determine the explosive-carrying intruder's coordinates, x and y.

$$y = \frac{\sum S_i Y_i}{\sum S_i}\ ,\ x = \frac{\sum S_i X_i}{\sum S_i} \tag{14}$$

As the simulation also considers more than one humans (without explosives) in the environment, the distinction of a "different human" is made by evaluating the traveled distance in the expired time interval in terms of its feasibility for a human-being. The same approach is applied for the determination of coordinates using the sound and pressure sensors.

4 - Simulation Environment

In the simulation, a hub unit and randomly deployed fifty sensor modules are considered in a 10 by 10 square meter area. The area is assumed to have no air draft, no boundaries, hence no reflection effects. The environment temperature and the velocity of sound throughout the simulations are assumed to be constant. It is also assumed that the 2 humans (one carrying explosives) are emitting sound waves periodically.

At this point of the studies, it is also assumed that the location of each sensor module and hub unit is known. Each module in the 50-sensor network consists of an odor sensor, microphone, accelerometer and pressure sensor. The total simulation time is 50 seconds, with the sampling times for sound/pressure/ accelerometers taken as 0.01 sec and that of odor sensors (with a slower response) taken as 1sec. In these results, data fusion is performed using a Least Square Estimation algorithm, which fuses all odor signals and motion signals separately combining data coming from sensors of the same type. However, a decision-making process which evaluates odor and motion signals together is also performed in determining the motion of the "mobile" explosive and separating it from the trajectory of the unarmed human.

In the simulation results, the motion of sound and odor diffusion is taken into consideration with the following models:

5 - Simulation Results

The simulation results for the detection and tracking of the explosive-carrying human (in an environment where an innocent human is also walking around) are given in Figure 13. In the figures, the *'s indicate the location of the sensor modules; the straight lines indicate the actual trajectories of the humans in the environment; the dark grey triangles represent the estimated trajectory of the innocent human and light grey triangles represents that of the explosive-carrying human; finally the black circles indicate the trajectory of the "mobile" explosive estimated based on data collected from the odor sensors only.

In Figure 13a we see two people walking parallel in north east direction. People at the south has bomb. It is easily seen that algorithm find the correct person easily. In Figure 13b we see two people walking in parabolic trajectory from west to east. And the person at the north has bomb. In the figure we can predict the person who has the bomb. And we also see that we should trace the peoples before we sense the odor and use these data. Because the odor diffuse too slowly. In Figure 13c we simulate two person one of them is walking to north east directly, and other one is walking on a spiral trajectory of increasing radius. And in Figure 13d both two people walking on the same kind of spiral trajectory. As it is easily seen that, the bomb can be easily detected again in these 2 case. In Figure 13e one person is walking to south west directly, and other one is walking to south east directly. And their trajectories are intersected. As seen in this Figure this case can also be determined. And in Figure 13f the people is walking on parabolic trajectory, which are intersected. As it is seen in the figure determining the person who has bomb get much more complicated, but still it can be done. Main problem is the speed of odor with respect to the intruder. So other sensors are getting a necessity.

The proposed odor sensor-based network activation strategy, which will obviously yield reduced energy consumption, is also analyzed in terms of mean square error(MSE) of tracking accuracy. With a trial simulation run using this strategy, only 20 sensors became active to track the "mobile" explosive. The strategy resulted in an MSE of 0.0205 as opposed to the conventional strategy keeping all 50 sensors in the network, yielding an MSE of 0.200. The very minor accuracy drop with this simplistic simulation run motivates the use of the proposed strategy in the actual network for energy optimization.

6 - Conclusions

Odor diffuses very slowly so we can easily say that, although accelerometers and sound sensors are more effective in tracking due to their fast response, odor sensors are effective in "detecting" the odor, but not in "tracking" due to their slow response.

Moreover, in a noisy environment, accelerometers could effectively assist the sound sensors. Non-uniformities of the ground are very effective on the performance of accelerometers; hence, sound sensors could be more efficient in such cases. Velocity of sound depends on ambient temperature, hence could benefit from calibration. Pressure sensors could serve this purpose. Pressure sensors have high accuracy, but low possibility of being stepped on. Therefore we can say that sensor fusion is needed supplying system more accurate and robust.

With the developed algorithm, it is possible to detect and track the target using data gathered from a minimum 3 sensors of the same type. However, using data also from different sensor types helps distinguishing the

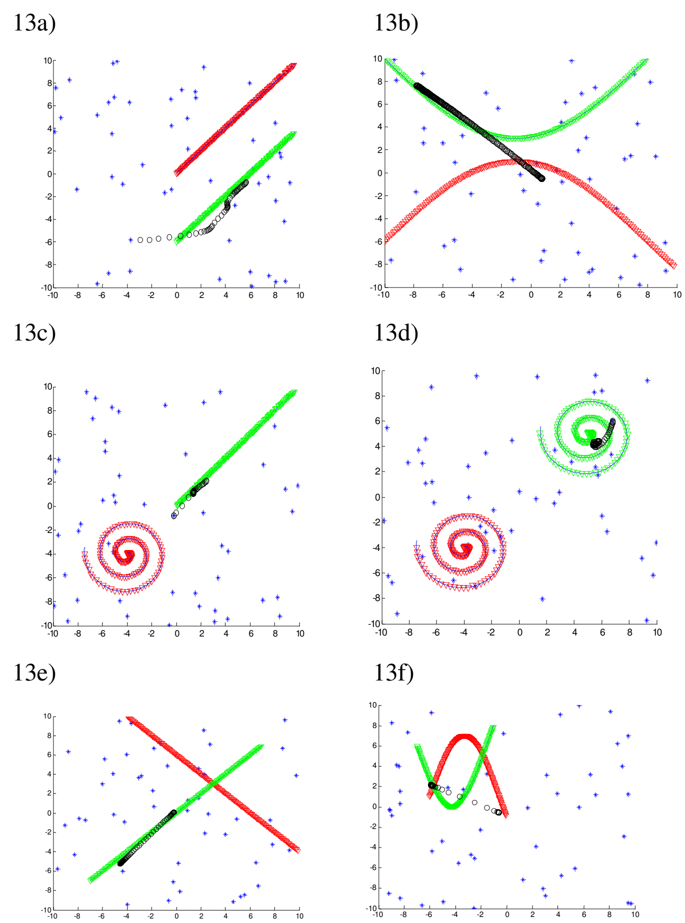

Figure 13. Simulation of the system by various trajectories.

With information obtained by fusing the data from each different sensor type, it is possible to exclude data that is not in harmony with data collected on the target. Hence, fusing the data coming from each sensor in the MEMS sensor modules with a scaling factor helps increase “target” detection and tracking. The evaluation of the multiple sensor data in relation to the odor sensor data is essential in the accurate tracking of the “mobile’ explosive in this study. Odor sensors are not only capable of the initial detection of the explosive, but also capable of serving as a somewhat slow guide in relating the detected odor to the possible trajectories with the help of the other sensors, as observed in the simulation results. Logic data coming from pressure sensors will act as a calibrator for position determination and contribute to accuracy. Odor sensor based network activation may possibly cause a small decrease in tracking accuracy, hence should be considered for reduced energy consumption in the network

Thus, the above combination of sensors will be considered in the preliminary design process of the MEM sensor module. While designing the MEM odor sensors, the decision on the choice of the supporting motion sensors will also be fine-tuned with more detailed and realistic simulation tasks given as student and/or master thesis projects.

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